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SOME COMPARISONS OF FOUR ORDER-ANALYTIC METHODS AND FACTOR ANALYSIS FOR ASSESSING DIMENSIONALITY

STEVEN L. WISE

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The first study in this report dealt with a comparison of three order analysis procedures: Krus & Bart's (1974) procedure and Reynolds' (1976) procedures using two of Cliff's (1977) consistency indices, c_{t1} and c_{t3}, respectively. The comparisons were based on seven simulated datasets with known factorial dimensionality, and two multidimensional sets of mathematics data. The c_{t3} procedure reproduced the factor structure for all of the simulated datasets, while the other two procedures performed very poorly. However, for the mathematics data, all three procedures failed to reproduce the factors.

The second study in this report presents preliminary results using a new order-analysis procedure which solves some of the difficulties with the other procedures in reproducing factorial dimensionality. This new procedure (dubbed ORDO) reproduced the factors for the mathematics data as well as for the simulated data. It is hoped that ORDO will represent a useful alternative to factor analysis for determining unidimensional item sets appropriate for latent-trait methods.

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SOME COMPARISONS OF FOUR ORDER-ANALYTIC METHODS AND FACTOR ANALYSIS FOR ASSESSING DIMENSIONALITY

Steven L. Wise

ABSTRACT

Current latent-trait methods require that the latent space underlying a group's test performance be unidimensional. However, many tests yield multidimensional data, implying that more than one latent trait would be necessary to account for test performance. A possible solution to this problem of multidimensionality would be to isolate unidimensional subsets of items from the total set of test items and use item response theory with each subset. While factor analysis is the most commonly proposed procedure for determining dimensionaltiy, a recently developed procedure called order analysis may also prove to be useful for isolating unidimensional item sets.

The first study in this report dealt with a comparison of three order analysis procedures: Krus & Bart's (1974) procedure and Reynolds' (1976) procedures using two of Cliff's (1977) consistency indices, c_{t1} and c_{t3}, respectively. The comparisons were based on seven simulated datasets with known factorial dimensionality, and two multidimensional sets of mathematics data. The c_{t3} procedure reproduced the factor structure for all of the simulated datasets,

while the other two procedures performed very poorly. However, for the mathematics data, all three procedures failed to reproduce the factors.

The second study in this report presents preliminary results using a new order-analysis procedure which solves some of the difficulties with the other procedures in reproducing factorial dimensionality. This new procedure (dubbed ORDO) reproduced the factors for the mathematics data as well as for the simulated data. It is hoped that ORDO will represent a useful alternative to factor analysis for determining unidimensional item sets appropriate for latent-trait methods.

Introduction

A major issue in item response theory concerns determining the number of latent dimensions (traits) needed to adequately account for the test performance of a group of individuals. If all of the relevant dimensions are not accounted for, then the requirement of local independence of items will not hold and the item response model will be intractable. This problem is compounded by current practical limitations of item response theory. While there have been multidimensional latent trait models proposed, estimation problems arising from these models have rendered them all but useless in the field. Hence, the current state of affairs regarding item response theory prevents one from considering more than one latent trait at a time. This means that the latent space under consideration has to be unidimensional in order to be practicable. However, many tests yield multidimensional data, implying that more than one latent trait would be necessary to account for test performance.

One possible solution to this problem of multidimensionality would be to extract unidimensional subsets of items from the larger, multidimensional set of items, and use item response theory to generate separate ability estimates from each subset. The most commonly prescribed method of determining the dimensionality of a set of items is factor analysis. However, Krus (1975) points out that factor analysis methods contain a considerable amount of indeterminancy due to a relative lack of consensus regarding such issues as (1) appropriate factor extraction method, (2) the problem of communality estimation, and (3) the number of factors to extract. Krus has suggested use of order analysis as an alternative to factor analysis in determining the dimensionality of a set of data.

Order analysis (Krus, Bart, & Airasian, 1975; Krus, 1975) was developed to investigate logical relations between the elements of a binary data matrix. The method presumes that elements measuring a single dimension show characteristics of a strong simple order,

i.e., that the relations between the elements are transitive, asymmetric, and connected (see Coombs, Dawes, and Tversky, 1970).

The relation of interest in order analysis is dominance. If a person fails item i and passes item j, then item i is said to dominate item j for that person. This follows from transitivity; since the person is dominated by item i (fails item i) and the person dominates item j (passes item j) then it is implied that item i dominates item j. This will be called an ij dominance.

If there is a one-dimensional latent attribute underlying the behavior reflected by the data, then the item relations will be consistent across persons (Coombs, et al., 1970). Hence, for any items i and j, all persons should show either an ij dominance, or they should all show a ji dominance. Lack of consistency across persons is in violation of the order-analytic model. However, since there are usually errors of measurement present in the data matrix, some amount of inconsistency is tolerated. Krus et al., (1975) proposed the use of McNemar's (1947) z statistic for correlated proportions to evaluate the preponderance of ij dominances over ji dominances. If the value of z is sufficiently large, then item i is concluded to dominate item j for the entire group. It is also assumed that the ji dominances are due to error. In the case where there is a single order present in the set of items, each item will dominate all items "below" it in the order, and transitivity, asymmetry and connectedness will all be realized. This set of items, also called a chain, will essentially form a Guttman scale.

There are times, however, when the z value between two items i and j does not indicate a clear ij dominance or ji dominance. This violates the connectedness property that there must be a relation between each pair of items in the order. According to Krus (1975), this indicates that items i and j are not members of the same order, and that the data are multidimensional. Based on this, a deterministic order-analytic model for determining the dimensionality of an item set was developed (Krus & Bart, 1974), and later a probabilistic model (Krus, 1977).

Cliff (1977) developed a number of indices to assess the consistency of simple orders. The first, c_{t1}, reflects the proportion of the total number of dominances in a dataset which are consistent with a particular ordering. Another important index, c_{t3}, is similar to c_{t1} except that it contains an adjustment for the number of dominances expected by chance for independent items. It is equivalent to Loevinger's (1947) index of homogeneity.

Reynolds (1976) rejected the approach of using McNemar's *z* test to evaluate the relation between items and then using the relations to generate item chains. He pointed out that Krus and Bart's (1974) deterministic method does not necessarily yield a unique set of item chains and that other, more "optimal" chains may also be extracted. Reynolds also noted that the Krus and Bart procedure lacked any goodness-of-fit statistics to evaluate how well an ordering is consistent across persons. Reynolds outlined an algorithm, using one of Cliff's (1977) consistency indices, to extract item chains. Each item in the set is used as a starting point in a chain. The most consistent items are then successively added to the chain until the overall chain consistency index value drops below some minimally acceptable level. Redundant chains are then deleted, and the remaining chains are interpreted as representing the dimensions of the dataset.

Earlier studies have failed to show a consistent relationship between the results of order analysis and factor analysis. Krus and Weiss (1976) found congruence between the two methods for Thurstone's 1947, p. 140-143) "box data". however, when they analyzed random data using Armstrong and Soelberg's (1968) method, they found differing results using order analysis and factor analysis. Bart (1978) reanalyzed the data reported in Bock and Lieberman (1970) and concluded that the factor structure of a set of data did not appear to relate in a clear way to the order structure.

Study I

The purpose of the first study was to compare different order-analysis procedures on a number of datasets with varying factorial dimensionality. Seven simulated dichotomous datasets were generated. These datasets differed both in terms of number of common factors and in terms of variance of the item difficulty levels. Also, two datasets composed of signed-numbers mathematics items (described more fully in Birenbaum and Tatsuoka (1980)) were used in comparing the order-analysis procedures. These analyses could aid in the understanding of the differences among the procedures, as well as providing insight regarding which procedure would be most useful in extracting sets of items which satisfy the unidimensionality assumption of current latent-trait models (Lord & Novick, 1968).

Method

Simulated Datasets

Seven simulated dichotomous datasets were generated using the FORMAL and TUCKLIB packages of FORTRAN subroutines at the University of Illinois. Each dataset, which consisted of 10 items and 500 persons, was computed as follows. A factor pattern matrix and a vector of uniquenesses were specified by the user. From this information a population variance-covariance matrix was generated using a modified Tucker, Koopman, and Linn (1969) procedure which simulated the effects of random error on the variance-covariance matrix by allowing for the influence of a number of minor random factors. This population variance-covariance matrix was then used in conjunction with a vector of user-specified population item means to generate dichotomous item scores from a multivariate normal population.

The seven simulated datasets are described in Table 1. It was decided that the distributions of item difficulty levels might have

Table 1

Descriptions of the Simulated Datasets

Dataset Label	Description (10 items, N=500)
H1	One factor with high spacing between the item means.
M1	One factor with moderate spacing between the item means.
L1	One factor with low spacing between the item means.
H2	Two factors with high spacing between the item means.
M2	Two factors with moderate spacing between the item means.
L2	Two factors with low spacing between the item means.
M10	Consisted of ten independent items with moderate spacing between the means (essentially a 10-dimensional dataset).

Table 2

Examples of the 16 Signed-Number Mathematics Skills

Item (Skill)	Example	Operation
1	1 - (-10) = 11	Subtraction
2	9 - (-7) = 16	Subtraction
3	-7 - 9 = -16	Subtraction
4	-12 - 3 = -15	Subtraction
5	-3 - 12 = -15	Subtraction
6	-6 - (-8) = 2	Subtraction
7	-16 - (-7) = -9	Subtraction
8	8 - 6 = 2	Subtraction
9	2 - 11 = -9	Subtraction
10	6 + 4 = 10	Addition
11	-14 + (-5) = -19	Addition
12	-5 + (-7) = -12	Addition
13	-3 + 12 = 9	Addition
14	-6 + 4 = -2	Addition
15	12 + (-3) = 9	Addition
16	3 + (-5) = -2	Addition

a differential effect on the order-analysis procedures. Hence, three types of item mean distributions were used: Highly spaced means where each item difficulty level is very distinct from that of the other items, moderately spaced means where some item difficulty levels are similar, and means which had the same population difficulty level but whose differences in sample difficulty levels were due only to random variation. Also, for the two-factor datasets (H2, M2, L2) items 1 - 4 always loaded on one factor, and items 5 - 10 loaded on the other factor.

Dataset M10 was unique in that it was generated so that there were no common factors among the items. It consisted of 10 unrelated items with moderately spaced means. This dataset was useful in comparing order-analysis procedures in their abilities to indicate a lack of order structure.

Mathematics Data

The mathematics dataset consisted of 16 dichotomous mastery scores derived from a 64-item signed-numbers test administered to 125 eighth grade students during November, 1979. There were 16 skills, each measured by four parallel items. Examples of these skills are shown in Table 2. If a student got a least three of the four items correct, he or she was deemed a master of that skill and given a mastery score of one. Otherwise, a score of zero was given (non-mastery).

Two forms of the mathematics dataset were analyzed. Birenbaum and Tatsuoka (1980) describe a procedure for detecting inappropriate strategies used by students in solving signed-number problems. Often, students can get "correct" answers to some of these problems using incorrect strategies. Once an incorrect strategy was detected for a given student, it was possible to determine the items for which the student would have given the correct answer using the inappropriate strategy. An "adjusted" dataset was then constructed from the original 64-item mathematics dataset such that items deemed to have been gotten

correct by an inappropriate strategy were rescored as incorrect. Dichotomous mastery scores were then recomputed for the adjusted dataset. Order analyses were subsequently performed on both the unadjusted (UMATH) and adjusted (AMATH) 16-item mastery datasets.

Order-Analysis Procedures

Three order-analysis procedures were used: the deterministic order-analysis method of Krus and Bart (1974), Reynolds' (1976) algorithm using c_{t1} as an extraction index, and Reynolds' procedure using c_{t3}. To determine the presence of a relation in Krus and Bart's procedure, a criterion McNemar's z value of 1.64 was used. Krus' (1977) probabilistic order-analysis procedure was not used for two reasons. First, it was decided that the results obtained from the deterministic and probabilistic models would be similar enough that both procedures would not be necessary in this study. Second, since Reynolds' (1976) method is deterministic, the deterministic order-analysis method was chosen in order to permit the most straightforward comparisons among the results of the different methods.

Results

Simulated Data

In order to verify the factor structures of the simulated datasets, simple common factor analyses of the matrices of phi coefficients were performed. For datasets where more than one common factor was extracted, factors were rotated using the Varimax criterion. The results of these factor analyses, along with the item means and standard deviations, are shown in Appendices 1 through 7. All seven datasets showed clear factorial dimensionality in agreement with the factor pattern matrices from which the datasets were generated. For dataset M10, a scree test of the eigenvalues led to the conclusion that no common factors were present.

Table 3

Item Chain Extraction for Datasets H1, M1, and L1

Dataset	Item Chains Extracted[1]: Krus & Bart Procedure	c_{t1} Procedure	c_{t3} Procedure	Overall Consistency Statistics: c_{t1}	c_{t3}	KR20
H1	(1-2-3-4-5-6-7-8-9-10)	(1-2-3-4-5-6-7-8-9-10)	(1-2-3-4-5-6-7-8-9-10)	.972	.944	.875
M1	(2-3-4-5-6-7) (1) (8) (9) (10)	(1-2-3-4-5-6-7-8-9-10)	(1-2-3-4-5-6-7-8-9-10)	.863	.901	.942
L1	(1) (2) (3) (4) (5) (6) (7) (8) (9) (10)	(1) (2) (3) (4) (5) (6) (7) (8) (9) (10)	(1-2-3-4-5-6-7-8-9-10)	.071	.745	.965

Note: Cutoff values of c_{t1} and c_{t3} used were .90 and .70, respectively.

1 - All of the items loaded on a single factor.

The order-analysis results for datasets H1, M1, and L1 are shown in Table 3. For H1, all three procedures correctly extracted a single chain (dimension) of items. For M1, the three procedures were not in agreement. While the single chain was correctly extracted using c_{t3}, use of the other two procedures yielded multiple chains. However, if the minimum consistency level of c_{t1} is lowered from .90 to .86, then the correct single chain would have been extracted for the c_{t1} procedure. For dataset L1, composed of items which were highly similar in terms of difficulty level, the c_{t3} procedure was the only procedure which extracted the single dimension. The other two procedures failed to determine any item chains. Note that the overall value of c_{t1} was near zero, while for c_{t3} it was fairly high.

Table 4 shows the order-analysis results for datasets H2, M2, and L2. For H2 Krus & Bart's (1974) procedure could not accurately extract the two factors. Items 6, 7, and 9 were incorrectly combined in a chain with items 1, 2, 3, and 4. Reynolds' procedure extracted the correct chains when either c_{t1} or c_{t3} was used. For M2, however, only the c_{t3} procedure extracted the two dimensions. The c_{t1} procedure extracted one of the dimensions, but could not extract the other. The results for Krus and Bart's procedure were chaotic in terms of the factor structure of this dataset. For dataset L2, as for L1, only the c_{t3} procedure correctly extracted the two dimensions. The other two procedures failed to combine any items into chains.

The chain extraction results for M10, shown in Table 5, illustrated other differences among the three procedures. In this dataset, there were no real common factors present among the items. The c_{t3} procedure extracted no chains at all. Krus and Bart's procedure, however, yielded a large (8-item) chain, and the c_{t1} procedure yielded a number of small chains.

Table 4

Item Chain Extraction for Datasets H2, M2, and L2

	Item Chains Extracted[1]			Overall Consistency Statistics		
Dataset	Krus & Bart Procedure	c_{t1} Procedure	c_{t3} Procedure	c_{t1}	c_{t3}	KR20
H2	(1-6-2-7-3-9-4)	(1-2-3-4)	(1-2-3-4)	.655	.393	.749
	(5-8-10)	(5-6-7-8-9-10)	(5-6-7-8-9-10)			
M2	(6-1-7-4-9)	(1-3-4-9)	(1-2-3-4)	.755	.374	.703
	(5-8-10)	(1-2-4-9)	(5-6-7-8-9-10)			
	(2)	(5-6-7-8-9-10)				
	(3)					
L1	(1)	(1)	(1-2-3-4)	.036	.329	.826
	(2)	(2)	(5-6-7-8-9-10)			
	(3)	(3)				
	(4)	(4)				
	(5)	(5)				
	(6)	(6)				
	(7)	(7)				
	(8)	(8)				
	(9)	(9)				
	(10)	(10)				

Note: Cutoff values of c_{t1} and c_{t3} used were .90 and .70, respectively.

1 - Items 1 - 4 loaded highly on one factor, and items 5 - 10 loaded highly on the other factor.

Table 5

Item Chain Extraction for Dataset M10

	Item Chains Extracted[1]			Overall Consistency Statistics		
Dataset	Krus & Bart Procedure	c_{t1} Procedure	c_{t3} Procedure	c_{t1}	c_{t3}	KR20
M10	(1-2-3-6-7-8-9-10)	(1-2-10)	(1)	.606	-.011	-.057
	(4)	(1-3)	(2)			
	(5)	(1-7)	(3)			
		(1-8)	(4)			
		(1-9)	(5)			
		(4)	(6)			
		(5)	(7)			
		(6)	(8)			
			(9)			
			(10)			

Note: Cutoff values of c_{t1} and c_{t3} used were .90 and .70, respectively.

1 - This dataset contained no common factors.

Mathematics Data

Factor analyses of the matrices of phi coefficients for the two mathematics datasets are shown in Tables 6 and 7. For the UMATH dataset, two-factor solution is presented, although a scree test of the eigenvalues did not clearly suggest the number of factors to extract. Factor solutions were obtained for two through five factors, and the two-factor solution best approximated simple structure. The subtraction items (1 - 9) comprised one factor, while four of the addition items (13 - 16) comprised the second factor. The four second-factor items were all skills dealing with the addition of two numbers that were opposite in sign.

However, when the data were adjusted for presumably erroneously correct responses (AMATH), two clear factors of subtraction and addition emerged. Only two eigenvalues were greater than one, and a very clear simple structure was present. The correlation between the two factors was .46.

Order analyses of the mathematics data, shown in Table 8, gave very different results from those of the factor analyses. For both datasets, neither the Krus & Bart procedure nor the c_{t1} procedure yielded chains that showed any resemblance to the factors. The c_{t3} procedure also failed to reproduce the factor structure for either dataset. For AMATH in particular, the c_{t3} procedure found one chain with fairly high overall consistency (c_{t3} = .764).

Discussion

It quickly became clear from the results of the simulated data that Krus & Bart's (1974) procedure did not perform very well in reproducing the factor structures of the datasets. The c_{t1} procedure did not fare much better; it reproduced the factor structures only for datasets H1 and H2. Basically there are two reasons for the poor results from these two procedures. First, when a factor contains two

Table 6

Simple Common Factor Analysis of Phi
Coefficients for the Unadjusted Mathematics (UMATH) Dataset

Item	Mean	S.D.	Factor I loadings	Factor II loadings	Eigenvalues
1	.648	.480	.817	-.119	5.449
2	.680	.468	.847	-.120	2.245
3	.584	.495	.696	-.078	1.665
4	.576	.496	.698	-.162	1.223
5	.720	.451	.891	-.096	1.028
6	.744	.438	.713	.082	.757
7	.824	.382	.617	.068	.712
8	.856	.352	.485	-.025	.545
9	.704	.458	.635	.118	.456
10	.992	.089	.119	.037	.407
11	.912	.284	.368	.159	.371
12	.936	.246	.352	.060	.338
13	.920	.272	.038	.765	.252
14	.944	.231	-.011	.591	.238
15	.920	.272	-.035	.509	.165
16	.920	.272	.051	.684	.150

Note: Factors were rotated using the Oblimin method.

Table 7

Simple Common Factor Analysis of Phi
Coefficients for the Adjusted Mathematics (AMATH) Dataset

Item	Mean	S.D.	Factor I loadings	Factor II loadings	Eigenvalues
1	.600	.492	.834	.015	8.216
2	.624	.486	.865	.007	2.881
3	.536	.501	.771	-.022	.836
4	.536	.501	.770	-.024	.682
5	.688	.465	.937	.030	.608
6	.664	.474	.895	.041	.501
7	.696	.462	.920	.050	.396
8	.792	.408	.679	-.068	.370
9	.648	.480	.749	.068	.347
10	.960	.197	.144	.353	.285
11	.888	.317	.108	.745	.251
12	.904	.296	.069	.786	.225
13	.888	.317	-.086	.858	.172
14	.896	.306	-.008	.850	.099
15	.872	.335	-.094	.814	.087
16	.880	.326	-.014	.833	.045

Table 8

Item Chain Extraction for the Mathematics Datasets

	Item Chains Extracted			Overall Consistency Statistics		
Dataset	Krus & Bart Procedure	c_{t1} Procedure	c_{t3} Procedure	c_{t1}	c_{t3}	KR20
UMATH	(4-1-5-7-11-10)	(4-5-11-12-10)	(4-3-1-2-5-6-11-12-10)	.678	.509	.866
	(3-2-8-15)	(3-5-11-12-10)	(4-1-5-6-7-8-10)			
	(9-13)	(1-2-12-10)	(9-11-12)			
	(6-16)	(3-5-14-10)	(5-14-10)			
	(12)	(9-12-10)	(13)			
	(14)	(4-8-10)	(15)			
		(1-7-10)	(16)			
		(6-10)	(12)			
		(13-10)				
		(15)				
AMATH	(3-1-6-8-15-10)	(3-4-6-5-7-11-12-10)	(3-4-1-2-9-6-5-7-8-15-16-11-13-14-12-10)	.777	.764	.936
	(4-2-5-16)	(3-6-5-7-14-12-10)				
	(9-11)	(1-2-5-7-11-12-10)				
	(7-13)	(4-6-5-8-10)				
	(14)	(2-7-16-10)				
	(12)	(9-14-10)				
		(5-13-10)				
		(15)				

Note: Cutoff values of c_{t1} and c_{t3} used were .90 and .70 respectively.

or more items with highly similar difficulty levels, all of these items will frequently not appear on the same chain. Items that are too close together in terms of difficulty will often fail to show a clear dominance relation, indicated by a low value of McNemar's $\underline{z}$. Hence, by Krus & Bart's procedure, this absence of a relation will imply that the items do not belong to the same dimension. Correspondingly, the low $\underline{z}$ value also means that c_{t1} between the items will also be very low. Thus, items similar in difficulty often show very inconsistent dominance relations.

The second problem with Krus & Bart's procedure and the c_{t1} procedure is also related to the distribution of item difficulty levels. Two items which are independent can show a consistent dominance relation which is due solely to difficulty differences between the two items. For example, consider two items that are independent and have difficulty levels of .30 and .90 computed from a sample of 100 persons. The expected number of dominances of item 1 over item 2 is equal to 100 x p(failing item 1 & passing item 2) = (100)(.70)(.90) = 63. Likewise, the expected number of dominances of item 2 over item 1 is equal to 3. In this case, $\underline{z} = 7.39$ and $c_{t1} = .91$. This illustrates that items that are disparate in difficulty will tend to show consistent dominance relations regardless of whether or not they belong to the same factor.

The value of c_{t3} for the above-mentioned example is 0. This illustrates a desirable property of c_{t3}, that the expected number of chance dominances (for independent items) is taken into consideration. The c_{t3} procedure is also less prone to the first problem described above that items too similar in difficulty level tend not to show a clear dominance relation.

The c_{t3} procedure yielded chains which correctly reflected the factor structures for all seven simulated datasets. It was found to be consistently superior to both the c_{t1} and Krus & Bart procedures. The better performance of c_{t3} compared with c_{t1} is in agreement with results found by Cudek (1980). However, for the mathematics data,

the c_{t3} procedure did a poor job of reproducing the factorial dimensionality. Two reasons are offered for this finding. First, the mathematics datasets showed a fairly strong first factor as evidenced by the magnitude of the first eigenvalues. The two-dimensional datasets showed no strong first factor. For the mathematics data, c_{t3} may have been unduly influenced by the first factor, which could have distorted the chain-extraction process. A second reason for the failure of c_{t3} to reproduce the factors for the mathematics data concerns the correlation between the factors. The factors for the simulated datasets were all orthogonal, whereas for the mathematics data the factors were substantially correlated (e.g. $r = .46$ for AMATH). In the case of correlated factors, the c_{t3} procedure may not be able to distinguish between items loading on different factors.

Study II

An attempt was made to develop a new order-analysis procedure which alleviated the problems of current procedures. Study I illustrated three major shortcomings of current order-analysis procedures for reproducing factorial dimensionality:

1) Items from the same factor with similar difficulty levels can be seen as being inconsistent (in the sense of showing about as many dominances as counter-dominances) and are therefore deemed to belong to different dimensions.
2) Two items that are independent can show a consistent dominance relation which is due solely to difficulty differences between the items.
3) Order analysis of a set of items with an oblique factor structure will often not reproduce the factorial dimensions.

The new order-analysis procedure, termed ORDO, was designed specifically to address the first two of these problems. Basically, ORDO represents an amalgamation of Krus and Bart's (1974) procedure and the Reynolds (1976) procedure using c_{t3}. Krus and Bart's approach seemed to be a good place to start in developing a new procedure, as it "truly" reflects the basic order-analytic principles of items (and persons) forming simple orders. Reynolds' procedure, on the other hand, deals with the consistency of an item set which is assumed to be an indicator of the orderability of the item set. In this sense, Reynolds' approach might be termed an indirect order-analysis procedure.

ORDO represents a radical departure from other order-analysis procedures in that it extracts partial orders of items rather than simple orders (see Coombs, et al., 1970). The connectedness property of simple orders creates the first problem with order-analysis procedures mentioned above. Considering dimensions as partial orders allows for two items to fall in the same dimension without there necessarily being a dominance relation between them. This may seem problematic, as the lack of a dominance relation between two items also represents the primary evidence that those items are from different dimensions. However, a pair of items from the same dimension that do not show a dominance relation have another characteristic -- high proximity. The proximity measure used is the squared Euclidean distance between the points representing the two items, which is also equal to the total number of persons for which one of the two items dominated the other. If two items are close together on the same dimension, few persons will pass only one of them. This high proximity characteristic is not evident for pairs of items which do not measure the same dimension.

The basic algorithm for ORDO proceeds as follows. Compute the item dominance matrix and reorder the rows and columns in terms of decreasing item difficulty level. Compute McNemar's z statistics for each item pair, as well as chi-square tests for association. If the values of z and chi-square are both significant then conclude

that a true relation (beyond that attributable to difficulty differences) exists between the two items. If either or both are not significant, then conclude that a true relation is not present. Next, use the relation information to extract a chain of items using Krus and Bart's (1974) method. This forms what is termed a "skeleton" chain of items. Items are then added to the chains that have high proximity to one of the skeleton chain members. This process results in each skeleton chain member and items added to it being considered as an equivalence class, where items between equivalence classes should how consistent dominance relations, and items within equivalence classes should not show consistent dominance relations. The chain-extraction process is then repeated for items which are not already members of a chain until all items are placed in a chain (singleton chains are allowed). The number of extracted chains is interpreted as the dimensionality of the dataset.

Method and Results

The simulated and mathematics datasets described in Study II were order-analyzed using ORDO. Although the results for the simulated data are not shown here, ORDO correctly reproduced the factors for all seven datasets. The results for the mathematics data are shown in Figures 1a and 1b. For the UMATH dataset, ORDO extracted four chains. Two of the chains were equivalent to the factors found for the two-factor solution given in Table 6. The four chains were labeled: subtraction, addition of two negative numbers, addition of two numbers with opposite signs, and addition of two positive numbers. For the AMATH dataset, ORDO extracted two chains which were clearly the same as the two factors of addition and subtraction. For both datasets, chains containing addition items showed few equivalence classes, due to highly similar means for those items.

ORDER I:
(Subtraction)

$$\begin{bmatrix} 4 \\ 3 \end{bmatrix} \longrightarrow \begin{bmatrix} 1 \\ 2 \end{bmatrix} \longrightarrow \begin{bmatrix} 5 \\ 9 \\ 6 \end{bmatrix} \longrightarrow \begin{bmatrix} 7 \\ 8 \end{bmatrix}$$

ORDER II:
(Addition of two negative numbers)

$$\begin{bmatrix} 11 \\ 12 \end{bmatrix}$$

ORDER III:
(Addition of numbers with opposite signs)

$$\begin{bmatrix} 13 \\ 14 \\ 15 \\ 16 \end{bmatrix}$$

ORDER IV:
(Addition of two positive numbers)

$$\begin{bmatrix} 10 \end{bmatrix}$$

Figure 1a: Order analysis results for UMATH dataset using ORDO (brackets denote equivalence classes, arrows denote dominances).

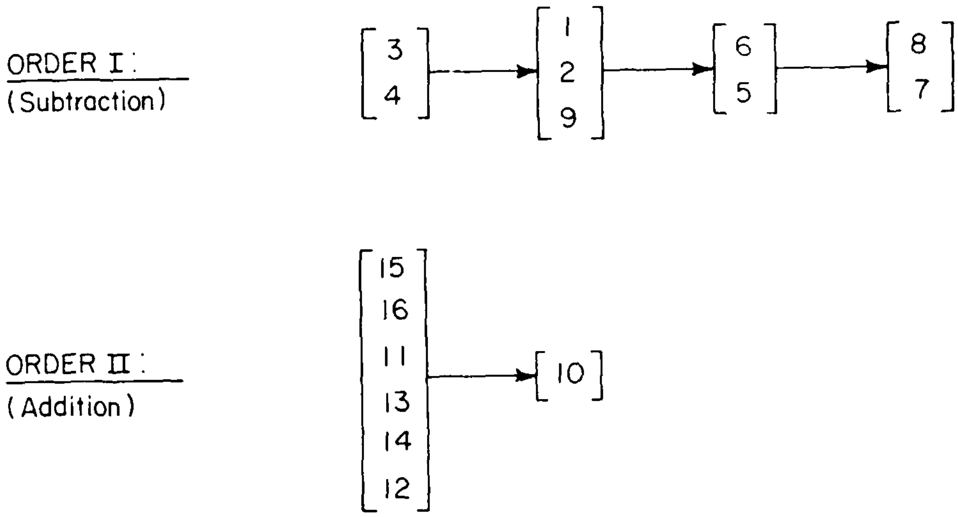

Figure 1b: Order analysis results for AMATH dataset using ORDO (brackets denote *equivalence classes, arrows denote dominances*).

Discussion

The results of this study support the use of ORDO as the order-analysis procedure to use in assessing the dimensionality of a test. ORDO matched the c_{t3} procedure in reproducing the factors present in the simulated data, and it outperformed the c_{t3} procedure in determining the factor structure of the mathematics data. Apparently, ORDO is less sensitive than the c_{t3} procedure to oblique factor structures and/or dominant first factors in a dataset.

The main motivation for extracting unidimensional subsets of items concerns satisfying the unidimensionality requirement of latent-trait models. Lord & Novick (1968) state that if performance on a set of items has an underlying multivariate normal distribution and a single common factor is present in a matrix of tetrachoric correlation coefficients, then the latent space is unidimensional and local independence holds. In this study, phi coefficients were used rather than tetrachoric coefficients. There are two persistent problems with tetrachoric correlation coefficients. When one item dominates another item in a perfectly consistent manner (i.e., no counterdominances) the tetrachoric correlation is equal to 1.0. However, since in most cases the correlation coefficient is calculated for sample data, one would typically be reluctant to accept 1.0 as a population correlation estimate. Also, matrices of sample tetrachoric coefficients will often be non-Gramian, in violation of basic assumptions of the factor-analytic model. Neither of these problems occur when phi coefficients are used. While phi coefficients are influenced by the relative difficulty levels of the items, Comrey (1973) reported finding the influences of difficulty factors to be minor, and he endorsed the use of phi rather than tetrachoric coefficients. Hence, phi coefficients were deemed to be appropriate in this study.

Order analysis avoids many of the problems involved in factor analysis. Also, no distributional assumptions are required in the order-analytic model. This study has shown that ORDO can yield

results that are highly similar to results found with factor analysis. Order analysis may represent a very desirable alternative to factor analysis in assessing the dimensionality of tests.

Certainly more research is necessary to determine the eventual usefulness of order analysis in determining item sets which are appropriate for item response theory.

References

Armstrong, J.W. & Soelberg, P. On the interpretation of factor analysis. Psychological Bulletin, 1968, 70, 361-364.

Bart, W.M. An empirical inquiry into the relationship between test factor structure and test hierarchical structure. Applied Psychological Measurement, 1978, 2(3), 331-335.

Birenbaum, M. & Tatsuoka, K.K. The use of information from wrong responses in measuring students' achievement (Research Report 80-1). Urbana, IL: Computer-based Education Research Laboratory, 1980.

Bock, R. & Lieberman, M. Fitting a response model of n dichotomously scored items. Psychometrika, 1970, 35, 179-197.

Cliff, N. A theory of consistency or ordering generalizable to tailored testing. Psychometrika, 1977, 42, 375-399.

Comrey, A.L. A first course in factor analysis. New York: Academic Press, 1973.

Coombs, C.H., Dawes, R.M., & Tversky, A. Mathematical Psychology: An Elementary Introduction. Englewood Cliffs (N.J.): Prentice Hall, 1970.

Cudck, R. A comparative study of indices for internal consistency. Journal of Educational Measurement, 1980, 17(2), 117-130.

Krus, D.J. Order analysis of binary data matrices. Los Angeles: Theta Press, 1975.

Krus, D.J. Order analysis: An inferential model of dimensional analysis and scaling. Educational and Psychological Measurement, 1977, 37, 587-601.

Krus, D.J. & Bart, W.M. An ordering theoretic method of multidimensional scaling of items. Educational and Psychological Measurement, 1974, 34, 525-535.

Krus, D.J., Bart, W.M., & Airasian, P.W. Ordering Theory and Methods. Los Angeles: Theta Press, 1975.

Krus, D.J. & Weiss, D.J. Empirical comparison of factor and order analysis on prestructured and random data. Multivariate Behavioral Research, 1976, 11, 95-104.

Loevinger, J. A systematic approach to the construction and evaluation of tests of ability. Psychological Monographs, 1947, 61(4, Whole No. 285).

Lord, F.M., & Novick, M.R. Statistical theories of mental test scores. Reading, MA: Addison-Wesley, 1968.

McNemar, Q. Note on the sampling error of the differences between correlated proportions of percentages. Psychometrika, 1947, 12(2), 153-157.

Reynolds, T.J. The analysis of dominance matrices: Extraction of unidimensional orders within a multidimensional context. (Technical Report No. 3). Los Angeles: University of Southern California, Department of Psychology, 1976.

Thurstone, L.L, Multiple Factor Analysis. Chicago: University of Chicago.Press, 1947.

Tucker, L.R., Koopman, R.F., & Linn R.L. Evaluation of factor analytic research procedures by means of simulated correlation matrices. Psychometrika, 1969, 34(4), 421-459.

Appendix 1

Factor Analysis Results for Dataset H1

	Mean	S.D.	Factor I loadings
1	.100	.300	.446
2	.196	.397	.611
3	.312	.464	.727
4	.424	.495	.791
5	.518	.500	.840
6	.608	.489	.810
7	.702	.458	.745
8	.810	.393	.609
9	.914	.281	.439
10	.996	.063	.110

Appendix 2

Factor Analysis Results for Dataset M1

Item	Mean	S.D.	Factor I loadings
1	.330	.471	.711
2	.322	.468	.699
3	.454	.498	.838
4	.480	.500	.851
5	.528	.500	.835
6	.566	.496	.845
7	.616	.487	.844
8	.744	.437	.757
9	.736	.441	.753
10	.756	.430	.722

Appendix 3

Factor Analysis Results for Dataset L1

Item	Mean	S.D.	Factor I loadings
1	.480	.500	.866
2	.490	.500	.877
3	.470	.500	.848
4	.480	.500	.845
5	.488	.500	.846
6	.480	.500	.856
7	.470	.500	.831
8	.474	.500	.854
9	.480	.500	.868
10	.464	.499	.856

Appendix 4

Factor Analysis Results for Dataset H2

Item	Mean	S.D.	Factor I loadings	Factor II loadings
1	.210	.408	-.049	.591
2	.396	.490	.043	.809
3	.592	.492	-.013	.808
4	.808	.394	-.035	.565
5	.242	.429	.639	-.006
5	.290	.454	.711	.046
7	.458	.499	.827	.011
8	.576	.495	.832	-.057
9	.716	.451	.736	-.027
10	.824	.381	.588	-.075

Appendix 5

Factor Analysis Results for Dataset M2

Item	Mean	S.D.	Factor I loadings	Factor II loadings
1	.226	.419	.083	.680
2	.416	.493	-.002	.857
3	.436	.496	-.002	.862
4	.718	.450	-.031	.578
5	.122	.328	.667	-.042
6	.106	.308	.633	-.054
7	.400	.490	.765	-.018
8	.404	.491	.762	-.030
9	.904	.295	.371	.073
10	.904	.295	.372	.048

Appendix 6

Factor Analysis Results for Dataset L2

Item	Mean	S.D.	Factor I loadings	Factor II loadings
1	.510	.500	-.010	.856
2	.500	.500	-.018	.832
3	.494	.500	-.013	.852
4	.496	.500	.016	.838
5	.498	.500	.839	.009
6	.522	.500	.848	-.005
7	.522	.500	.810	-.001
8	.512	.500	.848	-.015
9	.510	.500	.819	-.015
10	.498	.500	.839	-.012

Appendix 7

Factor Analysis Results for Dataset M10

Item	Mean	S.D.	Factor Number	Eigenvalue	% of Variance
1	.072	.259	1	1.18	11.8
2	.258	.438	2	1.17	11.7
3	.368	.483	3	1.11	11.1
4	.414	.493	4	1.07	10.7
5	.408	.492	5	0.99	9.9
6	.540	.499	6	0.99	9.9
7	.626	.484	7	0.95	9.5
8	.744	.437	8	0.87	8.7
9	.824	.381	9	0.85	8.5
10	.898	.303	10	0.82	8.2

Navy

1 Dr. Jack R. Borsting
Provost & Academic Dean
U.S. Naval Postgraduate School
Monterey, CA 93940

1 Dr. Robert Breaux
Code N-711
NAVTRAEQUIPCEN
Orlando, FL 32813

1 Chief of Naval Education and Training
Liason Office
Air Force Human Resource Laboratory
Flying Training Division
WILLIAMS AFB, AZ 85224

1 Dr. Richard Elster
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

1 DR. PAT FEDERICO
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152

1 Mr. Paul Foley
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. John Ford
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Henry M. Halff
Department of Psychology, C-009
University of California at San Diego
La Jolla, CA 92093

1 Dr. Patrick R. Harrison
Psychology Course Director
LEADERSHIP & LAW DEPT. (7b)
DIV. OF PROFESSIONAL DEVELOPMMENT
U.S. NAVAL ACADEMY
ANNAPOLIS, MD 21402

1 Psychologist
ONR Branch Office
Bldg 114, Section D
666 Summer Street
Boston, MA 02210

1 Psychologist
ONR Branch Office
536 S. Clark Street
Chicago, IL 60605

Navy

1 CDR Robert S. Kennedy
Head, Human Performance Sciences
Naval Aerospace Medical Research Lab
Box 29407
New Orleans, LA 70189

1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis (75)
Millington, TN 38054

1 Dr. William L. Maloy
Principal Civilian Advisor for
Education and Training
Naval Training Command, Code 00A
Pensacola, FL 32508

1 Dr. Kneale Marshall
Scientific Advisor to DCNO(MPT)
OP01T
Washington DC 20370

1 CAPT Richard L. Martin, USN
Prospective Commanding Officer
USS Carl Vinson (CVN-70)
Newport News Shipbuilding and Drydock Co
Newport News, VA 23607

1 Dr. James McBride
Navy Personnel R&D Center
San Diego, CA 92152

1 Ted M. I. Yellen
Technical Information Office, Code 201
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152

1 Library, Code P201L
Navy Personnel R&D Center
San Diego, CA 92152

6 Commanding Officer
Naval Research Laboratory
Code 2627
Washington, DC 20390

1 Office of Naval Research
Code 437
800 N. Quincy SStreet
Arlington, VA 22217

5 Personnel & Training Research Programs
(Code 458)
Office of Naval Research
Arlington, VA [illegible]17

Navy

1 Psychologist
ONR Branch Office
1030 East Green Street
Pasadena, CA 91101

1 Office of the Chief of Naval Operations
Research Development & Studies Branch
(OP-115)
Washington, DC 20350

1 LT Frank C. Petho, MSC, USN (Ph.D)
Code L51
Naval Aerospace Medical Research Laborat
Pensacola, FL 32508

1 Dr. Bernard Rimland (03B)
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Worth Scanland
Chief of Naval Education and Training
Code N-5
NAS, Pensacola, FL 32508

1 Dr. Robert G. Smith
Office of Chief of Naval Operations
OP-987H
Washington, DC 20350

1 Dr. Alfred F. Smode
Training Analysis & Evaluation Group
(TAEG)
Dept. of the Navy
Orlando, FL 32813

1 Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Ronald Weitzman
Code 54 WZ
Department of Administrative Sciences
U. S. Naval Postgraduate School
Monterey, CA 93940

1 Dr. Robert Wisher
Code 309
Navy Personnel R&D Center
San Diego, CA 92152

1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

Army

1 Technical Director
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Myron Fischl
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Dexter Fletcher
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria,VA 22333

1 Dr. Michael Kaplan
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Milton S. Katz
Training Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Harold F. O'Neil, Jr.
Attn: PERI-OK
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Mr. Robert Ross
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Robert Sasmor
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Commandant
US Army Institute of Administration
Attn: Dr. Sherrill
FT Benjamin Harrison, IN 46256

1 Dr. Frederick Steinheiser
U. S. Army Reserch Institute
5001 Eisenhower Avenue
Alexandria, VA [illegible]

Army

1 Dr. Joseph Ward
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force

1 Air Force Human Resources Lab
AFHRL/MPD
Brooks AFB, TX 78235

1 Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks AFB, TX 78235

1 Research and Measurment Division
Research Branch, AFMPC/MPCYPR
Randolph AFB, TX 78148

1 Dr. Malcolm Ree
AFHRL/MP
Brooks AFB, TX 78235

1 Dr. Marty Rockway
Technical Director
AFHRL(OT)
Williams AFB, AZ 58224

Civil Govt

1 Dr. Andrew R. Molnar
Science Education Dev.
and Research
National Science Foundation
Washington, DC 20550

1 Dr. Vern W. Urry
Personnel R&D Center
Office of Personnel Management
[illegible] E Street NW
Washington, DC 20415

1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC [illegible]

Marines

1 H. William Greenup
Education Advisor (E031)
Education Center, MCDEC
Quantico, VA 22134

1 Director, Office of Manpower Utilization
HQ, Marine Corps (MPU)
BCB, Bldg. 2009
Quantico, VA 22134

1 DR. A.L. SLAFKOSKY
SCIENTIFIC ADVISOR (CODE RD-1)
HQ, U.S. MARINE CORPS
WASHINGTON, DC 20380

Other DoD

12 Defense Technical Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC

1 Dr. William Graham
Testing Directorate
MEPCOM/MEPCT-P
Ft. Sheridan, IL 60037

1 Military Assistant for Training and
Personnel Technology
Office of the Under Secretary of Defense
for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301

1 MAJOR Wayne Sellman, USAF
Office of the Assistant Secretary
of Defense (MRA&L)
3B930 The Pentagon
Washington, DC 20301

1 DARPA
1400 Wilson Blvd.
Arlington, VA 22209

Coast Guard

1 Mr. Thomas A. Warm
U. S. Coast Guard Institute
P. O. Substation 18
Oklahoma City, OK [illegible]

Non Govt

1 Charles Myers Library
Livirgstone House
Livingstone Road
Stratford
London E15 2LJ
ENGLAND

1 Dr. Kenneth E. Clark
College of Arts & Sciences
University of Rochester
River Campus Station
Rochester, NY 14627

1 Dr. Norman Cliff
Dept. of Psychology
Univ. of So. California
University Park
Los Angeles, CA 90007

1 Dr. William E. Coffman
Director, Iowa Testing Programs
334 Lindquist Center
University of Iowa
Iowa City, IA 52242

1 Dr. Meredith P. Crawford
American Psychological Association
1200 17th Street, N.W.
Washington, DC 20036

1 Dr. Leonard Feldt
Lindquist Center for Measurment
University of Iowa
Iowa City, IA 52242

1 Dr. Richard L. Ferguson
The American College Testing Program
P.O. Box 168
Iowa City, IA 52240

1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850

1 Univ. Prof. Dr. Gerhard Fischer
Liebiggasse 5/3
A 1010 Vienna
AUSTRIA

1 DR. ROBERT GLASER
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 Dr. Erling B. Andersen
Department of Statistics
Studiestraede 6
1455 Copenhagen
DENMARK

1 1 psychological research unit
Dept. of Defense (Army Office)
Campbell Park Offices
Canberra ACT 2600, Australia

1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450

1 Dr. Werner Birke
DezWPs im Streitkraefteamt
Postfach 20 50 03
D-5300 Bonn 2
WEST GERMANY

1 Dr. Nicholas A. Bond
Dept. of Psychology
Sacramento State College
600 Jay Street
Sacramento, CA 95819

1 Dr. Robert Brennan
American College Testing Programs
P. O. Box 168
Iowa City, IA 52240

1 DR. C. VICTOR BUNDERSON
WICAT INC.
UNIVERSITY PLAZA, SUITE 10
1160 SO. STATE ST.
OREM, UT 84057

1 Dr. John B. Carroll
Psychometric Lab
Univ. of No. Carolina
Davie Hall 013A
Chapel Hill, NC 27514

1 Library
HumRRO/Western Division
27857 Berwick Drive
Carmel, CA 93921

1 Dr. Steven Hunka
Department of Education
University of Alberta
Edmonton, Alberta
CANADA

Non Govt

1 Dr. Earl Hunt
Dept. of Psychology
University of Washington
Seattle, WA 98105

1 Dr. Huynh Huynh
College of Education
University of South Carolina
Columbia, SC 29208

1 Professor John A. Keats
University of Newcastle
AUSTRALIA 2308

1 Mr. Marlin Kroger
1117 Via Goleta
Palos Verdes Estates, CA 90274

1 Dr. Charles Lewis
Faculteit Sociale Wetenschappen
Rijksuniversiteit Groningen
Oude Boteringestraat
Groningen
NETHERLANDS

1 Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

1 Dr. Frederick M. Lord
Educational Testing Service
Princeton, NJ 08540

1 Dr. Gary Marco
Educational Testing Service
Princeton, NJ 08450

1 Dr. Scott Maxwell
Department of Psychology
University of Houston
Houston, TX 77004

1 Dr. Samuel T. Mayo
Loyola University of Chicago
820 North Michigan Avenue
Chicago, IL 60611

1 Dr. Ron Hambleton
School of Education
University of Massechusetts
Amherst, MA 01002

Non Govt

1 Dr. Melvin R. Novick
356 Lindquist Center for Measurment
University of Iowa
Iowa City, IA 52242

1 Dr. Jesse Orlansky
Institute for Defense Analyses
400 Army Navy Drive
Arlington, VA 22202

1 Dr. James A. Paulson
Portland State University
P.O. Box 751
Portland, OR 97207

1 MR. LUIGI PETRULLO
2431 N. EDGEWOOD STREET
ARLINGTON, VA 22207

1 DR. DIANE M. RAMSEY-KLEE
R-K RESEARCH & SYSTEM DESIGN
3947 RIDGEMONT DRIVE
MALIBU, CA 90265

1 MINRAT M. L. RAUCH
P II 4
BUNDESMINISTERIUM DER VERTEIDIGUNG
POSTFACH 1328
D-53 BONN 1, GERMANY

1 Dr. Mark D. Reckase
Educational Psychology Dept.
University of Missouri-Columbia
4 Hill Hall
Columbia, MO 65211

1 Dr. Andrew M. Rose
American Institutes for Research
1055 Thomas Jefferson St. NW
Washington, DC 20007

1 Dr. Leonard L. Rosenbaum, Chairman
Department of Psychology
Montgomery College
Rockville, MD 20850

1 Dr. Chester Harris
School of Education
University of California
Santa Barbara, CA 93106

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
Champaign, IL 61820

Non Govt

1 Dr. Ernst Z. Rothkopf
Bell Laboratories
600 Mountain Avenue
Murray Hill, NJ 07974

1 Dr. Lawrence Rudner
403 Elm Avenue
Takoma Park, MD 20012

1 Dr. J. Ryan
Department of Education
University of South Carolina
Columbia, SC 29208

1 PROF. FUMIKO SAMEJIMA
DEPT. OF PSYCHOLOGY
UNIVERSITY OF TENNESSEE
KNOXVILLE, TN 37916

1 DR. ROBERT J. SEIDEL
INSTRUCTIONAL TECHNOLOGY GROUP
HUMRRO
300 N. WASHINGTON ST.
ALEXANDRIA, VA 22314

1 Dr. Kazuo Shigemasu
University of Tohoku
Department of Educational Psychology
Kawauchi, Sendai 980
JAPAN

1 Dr. Edwin Shirkey
Department of Psychology
University of Central Florida
Orlando, FL 32816

1 Dr. Robert Smith
Department of Computer Science
Rutgers University
New Brunswick, NJ 08903

1 Dr. Richard Snow
School of Education
Stanford University
Stanford, CA 94305

1 Professor Donald Fitzgerald
University of New England
Armidale, New South Wales 2351
AUSTRALIA

1 Dr. Edwin A. Fleishman
Advanced Research Resources Organ.
Suite 900
4330 East West Highway
Washington, DC 20014

Non Govt

1 Dr. Robert Sternberg
Dept. of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

1 DR. PATRICK SUPPES
INSTITUTE FOR MATHEMATICAL STUDIES IN THE SOCIAL SCIENCES
STANFORD UNIVERSITY
STANFORD, CA 94305

1 Dr. Hariharan Swaminathan
Laboratory of Psychometric and Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

1 Dr. Brad Sympson
Psychometric Research Group
Educational Testing Service
Princeton, NJ 08541

1 Dr. David Thissen
Department of Psychology
University of Kansas
Lawrence, KS 66044

1 Dr. Robert Tsutakawa
Department of Statistics
University of Missouri
Columbia, MO 65201

1 Dr. J. Uhlaner
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

1 Dr. Howard Wainer
Bureau of Social SCience Research
1990 M Street, N. W.
Washington, DC 20036

1 Dr. Phyllis Weaver
Graduate School of Education
Harvard University
200 Larsen Hall, Appian Way
Cambridge, MA 02138

1 DR. SUSAN E. WHITELY
PSYCHOLOGY DEPARTMENT
UNIVERSITY OF KANSAS
LAWRENCE, KANSAS 66044

1 Wolfgang Wildgrube
Streitkraefteamt
Box 20 50 03
D-5300 Bonn 2

END

DATE
FILMED
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